

Comparative Analyses of Land Use and Land Cover Dynamics From Landsat-8 OLI, ASTER LIT, and Sentinel-2A MSI Imageries over Selected LGAs in Osun State.

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abstract

Land use and land cover (LULC) mapping in tropical humid environments is frequently constrained by persistent cloud cover and complex landscape heterogeneity. This study comparatively evaluates the performance of Landsat-8 OLI (resampled to 15 m), ASTER LIT (15 m), and Sentinel-2A MSI (10/20 m) imageries for multi-temporal LULC mapping (2015, 2018, and 2024) across selected Local Government Areas in Osun State, Nigeria. Supervised image classification was executed using the Maximum Likelihood Classifier across six discrete land cover classes within ENVI, ERDAS Imagine, and ArcGIS Pro environments. The results demonstrate that Sentinel-2 achieved the highest overall classification accuracy (95.40%; Kappa = 0.89), followed by ASTER (92.50%; Kappa = 0.86) and Landsat-8 (91.70%; Kappa = 0.82). The superior discrimination of Sentinel-2 was supported by a higher Jeffries Matusita distance (1.96) between undisturbed and disturbed forest classes, driven by its 10 m spatial resolution and strategic red-edge spectral bands. However, McNemar's test revealed no statistically significant accuracy differences among sensor pairs ($p > 0.05$: Sentinel-2 vs. ASTER, $p = 0.0663$; Sentinel-2 vs. Landsat-8, $p = 0.0673$; ASTER vs. Landsat-8, $p = 0.0653$). While Sentinel-2 offered enhanced delineation of fragmented peri-urban areas, both ASTER and pan-sharpened Landsat-8 maintained high, comparable accuracies ($> 90\%$), confirming their continued reliability for long-term historical analyses in data-scarce tropical regions. These findings provide vital empirical benchmarks for sensor selection and sustainable land management in heterogeneous humid mosaics.

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1.0 Introduction

The contemporary era, frequently defined by the unprecedented scale of human-induced environmental transformation, has placed the monitoring of Land Use and Land Cover (LULC) at the centre of global sustainability discourse. The burgeoning global population, projected to reach near ten billion by mid-century, continues to exert significant pressure on terrestrial resources, manifesting in rapid urbanization, the conversion of primary forests into intensive agricultural matrices, and the degradation of fragile wetlands (Oluwatoyin et al., 2025).

These transformations are not merely physical shifts in surface features but represent fundamental alterations to the Earth's biogeochemical cycles, influencing carbon sequestration capacity, hydrological stability, and the preservation of biological diversity (Olanrewaju et al., 2025). In the specific context of West Africa, and Nigeria in particular, the rate of LULC change has been described as unprecedented. As Africa's most populous nation, Nigeria faces a unique convergence of demographic expansion and socioeconomic development, which has led to dramatic shifts in its landscape configuration. Remote sensing technology provides the most viable, scalable, and cost-effective solution for monitoring these changes across large and often inaccessible regions (Benewinde et al., 2015).

The Landsat program has provided a foundation for long-term spatial analysis

since the 1970s, the emergence of high-resolution, free-access data from the European Space Agency's Sentinel-2 mission and the continued utility of instruments like the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) have introduced new possibilities for multi-sensor integration and comparative performance evaluation (Oykhonor et al., 2024). Understanding these dynamics in Osun State, situated in the Southwestern region of Nigeria, is paramount for effective regional planning, climate change mitigation, and the management of natural resources. The state, characterized by a transition from lush tropical rainforest to derived savanna, serves as a critical testbed for evaluating the performance of diverse remote sensing algorithms under complex and heterogeneous classification conditions (Muhammad, et al., 2023). This study provides an exhaustive analysis of the spatial-temporal dynamics of land cover in Osun State between 2015 and 2024, specifically evaluating the comparative capabilities of Landsat-8 OLI, ASTER LIT, and Sentinel-2A MSI.

Recent meteorological investigations, such as those conducted during the Dynamics-Aerosol-Chemistry-Cloud Interactions in West Africa (DACCWA) campaign, have highlighted the prevalence of daytime low-level clouds (LLCs) within the first 2km of the atmosphere over West Africa (Derrick et al., 2019). These LLCs, consisting of both nocturnal low stratus clouds that persist into the early afternoon and shallow convective cumulus clouds, significantly block incoming shortwave radiation (Derrick, et al., 2020). In the Guinean region of West Africa, it has been estimated that approximately 49% of the downwelling surface shortwave radiation is lost on

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average during the peak monsoon months due to these cloud systems (Cyrielle et al., 2020).

For optical satellite sensors, this high frequency of cloud cover lowers the number of available cloud-free observations, often resulting in significant data gaps during critical stages of the vegetation growing season (Gomez et al., 2016). Even when images are available, sub-pixel clouds and cloud shadows introduce radiometric noise, which can obscure subtle land cover signals or lead to the misclassification of vegetation as degraded or bare land. The dynamic nature of the climate in the Niger Delta and broader South-western Nigeria means that satellite imagery acquired even in the "dry" season can have cloud cover as high as 32%, as observed in Landsat-8 acquisitions over the region in 2019 (Uchegbulam et al., 2021).

This necessitates the use of sophisticated cloud-masking algorithms and atmospheric correction techniques to ensure the reliability of LULC classification results.

Beyond cloud cover, the atmosphere over West Africa is characterized by high aerosol loading from both natural and anthropogenic sources. Mineral dust from the Sahara and biomass burning aerosols from agricultural activities and domestic fires significantly alter the radiation budget through scattering and absorption of solar radiation (Cyrielle, et al., 2020). These aerosols undergo physical and chemical aging processes during transport, which further modifies their optical properties and complicates the retrieval of surface reflectance. The spectral variability of the single-scattering albedo (SSA) is mainly controlled by aerosol composition rather than size distribution, with black carbon particles being the dominant absorber in the visible range. Without rigorous atmospheric correction, such as the use of the Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) or Dark Object Subtraction (DOS) methods, these atmospheric effects can lead to substantial errors in spectral classification (Mahesh & Kapil 2017).

To address the complexities of the tropical landscape, the geoinformatics community has relied on a suite of satellite systems, each possessing unique spatial, spectral, and radiometric configurations. A comparison of the technical specifications of Landsat-8, ASTER, and Sentinel-2 reveals the relative strengths and limitations of these platforms in resolving heterogeneous features.

The Landsat mission, jointly operated by the USGS and NASA, remains the only satellite data record that enables multidecadal land cover assessment at a medium spatial resolution. Landsat-8, launched in 2013, introduced the Operational Land Imager (OLI), which represented a significant departure from the whiskbroom scanners of previous generations. The OLI sensor employs a pushbroom architecture with a long detector array that sweeps across the ground, providing a significantly higher signal-to-noise ratio (SNR) and improved radiometric (Peter, et al., 2022).

The OLI sensor collects 12-bit data (compared to the 8-bit quantization of Landsat-7), which enables the detection of finer brightness values and reduces the likelihood of saturation in bright features like bare soil or urban rooftops. Its spectral bands are designed to capture specific wavelengths with narrow bandwidths to minimize atmospheric absorption. For instance, the inclusion of a coastal/aerosol band (0.435 - 0.451nm) assists in the detection of atmospheric haze, while the cirrus band (1.363 - 1.384nm) is essential for masking semi-transparent clouds that might otherwise contaminate surface reflectance values. Despite these advancements, the standard 30-meter resolution of Landsat multispectral bands remains a challenge for urban built-up extraction in the fragmented peri-urban areas of Nigeria, where small residential structures are often smaller than the pixel footprint.

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), carried on NASA's Terra satellite, provides a versatile set of multispectral bands spanning from the visible to the thermal infrared. ASTER's visible and near-infrared (VNIR) subsystem provides three bands at a 15-meter spatial resolution, which is superior to Landsat's standard 30-meter multispectral data (Tingbin, et al., 2016). This intermediate resolution is particularly effective for mapping forest fragments and riparian vegetation in the humid tropics.

However, ASTER's primary advantage lies in its shortwave infrared (SWIR) and thermal infrared (TIR) subsystems. With six SWIR bands at 30-meter resolution and five TIR bands at 90-meter resolution, ASTER has historically been the sensor of choice for lithological discrimination and mineral mapping. In LULC applications, the SWIR bands are highly effective for predicting the

occurrence of specific mineral groups and moisture-stressed vegetation. While the ASTER SWIR cooling system failure in 2008 limited the availability of high-quality SWIR data in more recent years, the L1T products (precision terrain corrected) remain a robust source for comparative spatial analysis when combined with VNIR data (Mahesh & Kapil 2017).

The Sentinel-2 mission, part of the European Copernicus program, has established a new paradigm in land monitoring by providing high-resolution, wide-swath multispectral imagery with a high revisit frequency. Each Sentinel-2 satellite carries the Multi-Spectral Instrument (MSI), providing 13 spectral bands at spatial resolutions of 10, 20, and 60 meters.

The most significant spectral innovation of Sentinel-2 is the inclusion of three spectral bands in the "red-edge" region, centered at 705, 740, and 783 nm (Steven et al., 2011). The red-edge is the spectral region where the reflectance of green vegetation rises rapidly, and it is highly sensitive to biophysical parameters such as green leaf area index (LAI), chlorophyll content (Ch), and canopy nitrogen levels. While standard indices like the Normalized Difference Vegetation Index (NDVI) often saturate in high-biomass tropical forests, red-edge-derived indices remain sensitive to variations in canopy structure and health. This spectral sensitivity, combined with the 10-meter spatial resolution of its core visible and NIR bands, allows Sentinel-2 to detect smaller features such as isolated rural buildings or narrow forest paths that are lost in the 30-meter pixels of Landsat (Jesus et al., 2011).

The aim of this study is to compare the effectiveness of these three distinct datasets; Landsat 8 (30m/15m), ASTER (15m), and Sentinel-2 (10m/20m) in accurately mapping LULC classes within the ecologically and socio-economically diverse region of Osun State. Given the region's challenges with cloud contamination and highly mixed land cover pixels, a robust comparative analysis of sensor performance is necessary to inform future monitoring efforts.

While numerous studies have compared these sensors, a comprehensive multi-temporal evaluation of Landsat 8, ASTER, and Sentinel-2 performance for LULC mapping in the highly heterogeneous and persistently cloud-affected tropical humid environment of Osun State, Nigeria, is unavailable. This study uniquely addresses the challenge of selecting optimal satellite data for LULC monitoring under such demanding conditions, offering insights into sensor-specific strengths and limitations that are particularly relevant for regions facing similar environmental constraints

The primary objectives of the study are:

1. to generate LULC maps for 2015, 2018, and 2024 using Landsat 8, ASTER, and Sentinel-2 imagery.
2. to offer a comparative evaluation of the classification accuracy of the Maximum Likelihood Classifier (MLC) across the three sensor types.
3. to analyse the spatial and temporal LULC changes in the selected Local Government Areas (LGAs) of Osun State over the nine-year period.

2.0 Study Area

The study focuses on selected Local Government Areas (LGAs) within Osun State, situated in the Southwestern region of Nigeria. The (LGAs) includes; Iwo, Aiyedire, Ota-Oluwa, Ejigbo, Orotu, Erepodun, Egbedore, Ede North and Oforunda as shown in figure 1.0. The region is characterized by a tropical humid climate and diverse ecosystems, including rainforest, derived savanna, and extensive agricultural mosaics. This environment presents an ideal testbed for evaluating the performance of remote sensing algorithms under complex classification conditions.

2.1 Satellite Data Acquisition

The following satellite imagery was utilized for the analysis, corresponding to the years 2015, 2018, and 2024: Sensor Spatial Resolution (m) Key Bands Utilized Landsat 8 OLI 30 (Multispectral), 15 (Panchromatic) Visible, Near-Infrared (NIR), Shortwave Infrared (SWIR) Temporal Coverage 2015, 2018, 2024 ASTER LIT Sentinel-2A MSI 15 (VNIR) 10 (Visible, NIR), 20 (SWIR) Visible, Near-Infrared (NIR) Visible, Near-Infrared (NIR), Shortwave Infrared (SWIR) 2015, 2018, 2024 2015, 2018, 2024. All images were selected for minimal cloud cover over the study area, acquired during the dry season to minimize atmospheric effects, and subjected to standard atmospheric and radiometric corrections using the FLAASH algorithm built on MODTRAN in a commercial tool (ENVI) that corrects for the adjacency effect (light reflecting from nearby pixels). This approach is best used in Urban areas or high-contrast scenes in LULC classification studies.

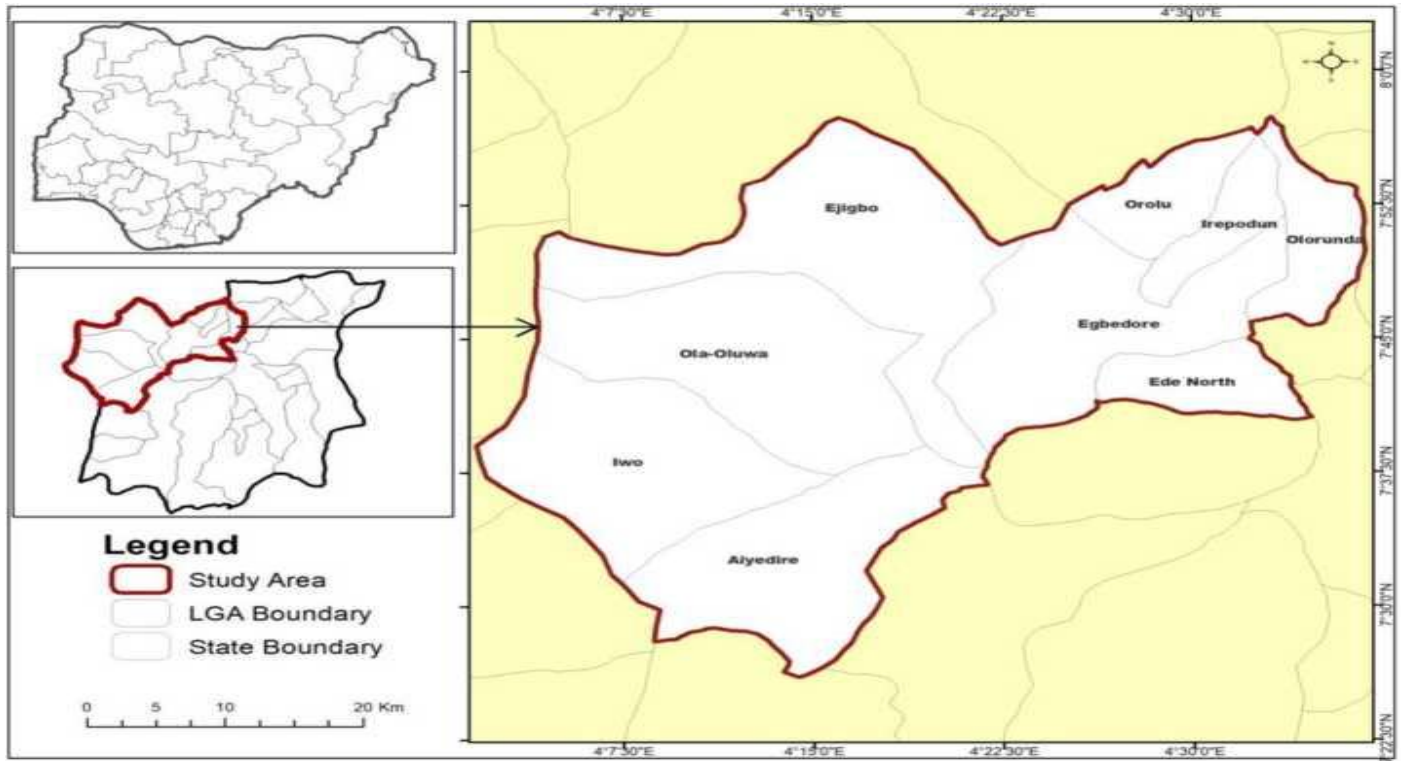


Figure. 1.0 Map of the Study Area

Table 1.0: Spectral Bands of Landsat 8/9 Operational Land Imager (OLI/TIRS)

Bands	Wavelength (micrometers)	Resolution (meters)
Band 1 - Ultra Blue (coastal/aerosol)	0.435 - 0.451	30
Band 2 - Blue	0.452 - 0.512	30
Band 3 - Green	0.533 - 0.590	30
Band 4 - Red	0.636 - 0.673	30
Band 5 - NIR	0.851 - 0.879	30
Band 6 - SWIR 1	1.566 - 1.651	30
Band 7 - SWIR 2	2.107 - 2.294	30
Band 8 - Panchromatic	0.503 - 0.676	15
Band 9 - Cirrus	1.363 - 1.384	30
Band 10 - Thermal 1	10.60 - 11.19	100* (30)
Band 11 - Thermal 2	11.50 - 12.51	100* (30)

Table 1.1: Spectral Bands and Information of ASTER LIT

Band	Label	Wavelength (μm)	Resolution (m)	Nadir or backward	Description
B1	VNIR_Band1	0.520 - 0.60	15	Nadir	Visible green/yellow
B2	VNIR_Band2	0.630 - 0.690	15	Nadir	Visible red
B3N	VNIR_Band3N	0.760-0.860	15	Nadir	Near infrared
B3B	VNIR_Band3B	0.760-0.860	15	Backward	
B4	SWIR_Band4	1.600-1.700	30	Nadir	Short-wave infrared
B5	SWIR_Band5	2.145-2.185	30	Nadir	
B6	SWIR_Band6	2.185-2.225	30	Nadir	
B7	SWIR_Band7	2.235-2.285	30	Nadir	
B8	SWIR_Band8	2.295-2.365	30	Nadir	
B9	SWIR_Band9	2.360-2.430	30	Nadir	
B10	TIR_Band10	8.125-8.475	90	Nadir	Long-wave infrared or thermal IR
B11	TIR_Band11	8.475-8.825	90	Nadir	
B12	TIR_Band12	8.925-9.275	90	Nadir	
B13	TIR_Band13	10.250-10.950	90	Nadir	
B14	TIR_Band14	10.950-11.650	90	Nadir	

Table 3.1: Properties of ASTER data acquired

S/N	PRODUCT TYPE	RESOLUTION (m)	BAND	DATE
1.	AST_L1T_00301042015010142_20150619063250_V	15	3-2-1	2015/06/19
2.	AST_L1T_00301062018102028_20180107111141_V	15	3-2-1	2018/01/07
3.	AST_L1T_00301292024094320_20240130070302_V	15	3-2-1	2024/01/30

Table 3.2: Properties of LANDSAT data acquired

S/N	PRODUCT TYPE	RESOLUTION (m)	BAND	DATE
1.	LC08_L1TP_190055_20150115_20200910_02_T1	30 resample to 15m	5-4-3	2015/01/15
2.	LC08_L1TP_190055_20180123_20200902_02_T1	30 resample to 15m	5-4-3	2018/01/23
3.	LC09_L1TP_190055_20240116_20240116_02_T1	30 resample to 15m	5-4-3	2024/01/16

Table 3.3: Properties of Sentinel-2 data acquired

S/N	PRODUCT TYPE	RESOLUTION(m)	BAND	DATE
1.	S2A_MSIL1C_20151208T100412_N0500_R122_T31NFJ.SAFE	20	8-4-3	2015/12/08
2.	S2A_MSIL1C_20180116T100341_N0500_R122_T31NFJ_.SAFE	20	8-4-3	2018/01/16
3.	S2B_MSIL1C_20240120T100239_N0510_R122_T31NFJ_.SAFE	20	8-4-3	2024/01/20

3.0 Methodology

The methodology encompasses image pre-processing, development of a consistent classification scheme, application of the classification algorithm, and rigorous accuracy assessment. The entire workflow was executed using a combination of commercial geospatial software: ENVI, ERDAS IMAGINE, and ARCGIS PRO.

3.1 Pre-processing and Pan-sharpening

All acquired images were corrected for geometric distortion and atmospherically corrected to surface reflectance values. A key pre-processing step involved improving the spatial resolution of the Landsat 8 data. The 30-

meter multispectral bands were resampled to 15 meters using the sensor's high-resolution panchromatic band (Band 8). The nearest neighbour resampling technique was specifically employed to preserve the original radiometric values of the pixels, which is critical for the subsequent spectral classification (Steven et al., 2011).

Pre-processing ensures that the spectral signatures used in algorithms like Maximum Likelihood Classification are representative of the actual land cover rather than atmospheric noise. Pan-sharpening provides finer spatial detail, allowing for the identification of smaller features like individual buildings, smaller crop land, or specific trees or water bodies that would be blurred in standard multispectral imagery.

Table 3.4: Comparison of Pan-sharpening algorithms

Feature	Nearest Neighbor	Bilinear Interpolation	Cubic Convolution
Spectral Integrity	Excellent (Original values)	Moderate (Averaged)	Low (Smoothed/Overshot)
Spatial Appearance	Poor (Blocky/Jagged)	Smooth	Sharpest
Processing Speed	Fastest	Moderate	Slow
Best Used For	Spectral Analysis, Parametric Classifiers	General Mapping, Visualization	High-end Visual Interpretation

Table 3.5: Shapiro-Wilk (W) test for Normality

Class	Band	W-Statistic	p-value	Normal? (p > 0.05)
Bare Land	Band 1	0.9813	0.6087	Yes
Disturbed Forest	Band 2	0.9765	0.5123	Yes
Undisturbed Forest	Band 3	0.9536	0.5846	Yes
Water Body	Band 1	0.9412	0.0141	No
Built-Up Area	Band 2	0.8245	0.0001	No
Cropland/Agriculture	Band 3	0.9352	0.6024	Yes

The goal of this study is to achieve high-accuracy in spectral analysis; the nearest neighbour resampling technique was therefore preferred because it maintains the radiometric relationships between bands (as indicated in table 3.5).

3.2 Classification Scheme

Owing to the heterogeneous and fragmented nature of the LULC in Osun State, a detailed yet manageable scheme of six discrete classes was adopted:

1. Undisturbed Forest: Dense canopy cover with minimal human intervention.
2. Disturbed Forest: Degraded Forest areas, often characterized by selective logging or proximity to human settlements.
3. Cropland/Agriculture: Actively managed agricultural fields and perennial crops.
4. Water Body: Rivers, reservoirs, and perennial water features.
5. Built-up Area: Residential, commercial, and industrial infrastructure.
6. Bare Land: Exposed soil, construction sites, or newly harvested areas.

3.3 Test for Normality of Training Data

The Shapiro-Wilk test calculates a W statistic that tests the null and Alternative hypothesis (H0) and (Ha) to investigate the normality of the distribution of a set of data.

Null Hypothesis (H0): “The sample comes from a normal distribution”.

Alternative Hypothesis (Ha): “The sample does not come from a normal distribution”.

The result of the Shapiro-Wilk (W) test returning a p value > 0.05 in many bands of different classes as shown in table 3.4, the Null Hypothesis H0 is not rejected and this justifies the Maximum Likelihood Classifier as a better choice compared to non-parametric models like Random Forest or Support Vector Machines (SVM), given the heterogeneous and fragmented nature of the Land Use Land Cover classification adopted for this study.

3.3 Supervised Classification (Maximum Likelihood Classifier)

Maximum Likelihood Classification (MLC) was selected as the supervised algorithm for its widespread use and statistical robustness, assuming that the statistics for each class in each band are normally distributed. Training samples (Regions of Interest) were collected from high-resolution imagery (Google Earth) and field knowledge, ensuring a uniform set of training data was used across the three sensor types for the comparative analysis. The MLC technique calculates the probability of a pixel belonging to a specific class based on the mean and covariance matrix of the training data (Yan-Cheng, et al., 2024).

The algorithm calculates the probability that a given pixel belongs to a specific class. The pixel is then assigned to the class that has the highest maximum likelihood.

1. Training Stage: We provided "training sites" such as representative samples of land cover types like water, forest, or urban classes.
2. Statistical Calculation: The MLC calculates a mean vector and a covariance matrix for each class based on the training data.
3. Probability Surface: For every pixel in the image, the algorithm evaluates the multidimensional spread of the classes.
4. Assignment: It considers both the distance of a pixel from the class mean and the variability of that class to determine the final label.

S/N	Class Type	Description
1.	Bare Land	Bare exposed rock and soil, un-vegetal land, degraded lands, and mixed barren land
2.	Built-Up Area	Areas selected as residential, commercial, industrial, and transportation facilities
3.	Cropland/Agriculture	Agricultural croplands, cultivated lands, and agricultural fallow lands
4.	Disturbed Forest	Shrubs, grassland, mixed rangeland, riparian vegetation and riparian forestry
5.	Undisturbed Forest	Deciduous natural forest land, evergreen trees, mixed forest land
6.	Water Body	Rivers, streams, and ponds

4.0: Results and Discussion

This section presents the results of the Land Use/Land Cover (LULC) classification analysis conducted for selected Local Government Areas (LGAs) in Osun State, Nigeria, covering three temporal periods: 2015, 2018, and 2024. The analysis employed three different satellite datasets—ASTER, Landsat-8, and Sentinel-2 using supervised classification techniques. The classification was performed using three software platforms: ENVI, ERDAS Imagine, and ARCGIS PRO. This multi-sensor, multi-temporal approach provides a comprehensive understanding of the spatial and temporal dynamics of land cover changes in the study area (Oluwatobi, et al., 2025).

4.1 ASTER Land Use/Land Cover Analysis

Temporal Distribution of LULC Classes (2015-2024) revealed six major land cover classes across the study area of 1,952.9 km². Table 4.1 and figure 4.1 present the areal extent of each land cover class for the three time periods analysed and the classification maps for 2015, 2018, and 2024 respectively.

Table 4.1: Area covered (km²) by ASTER Land Use/Land Cover classification features

Feature Class	2015 (km ²)	2018 (km ²)	2024 (km ²)
Water Body	10.2	8.8	9.8
Undisturbed Forest	759.6	529.1	764.6
Disturbed Forest	225.5	266.2	643.7
Cropland/Agriculture	785.9	786.6	257.0
Built-Up Area	133.7	209.6	257.9
Bare Land	37.9	152.6	19.9
Total	1,952.9	1,952.9	1,952.9

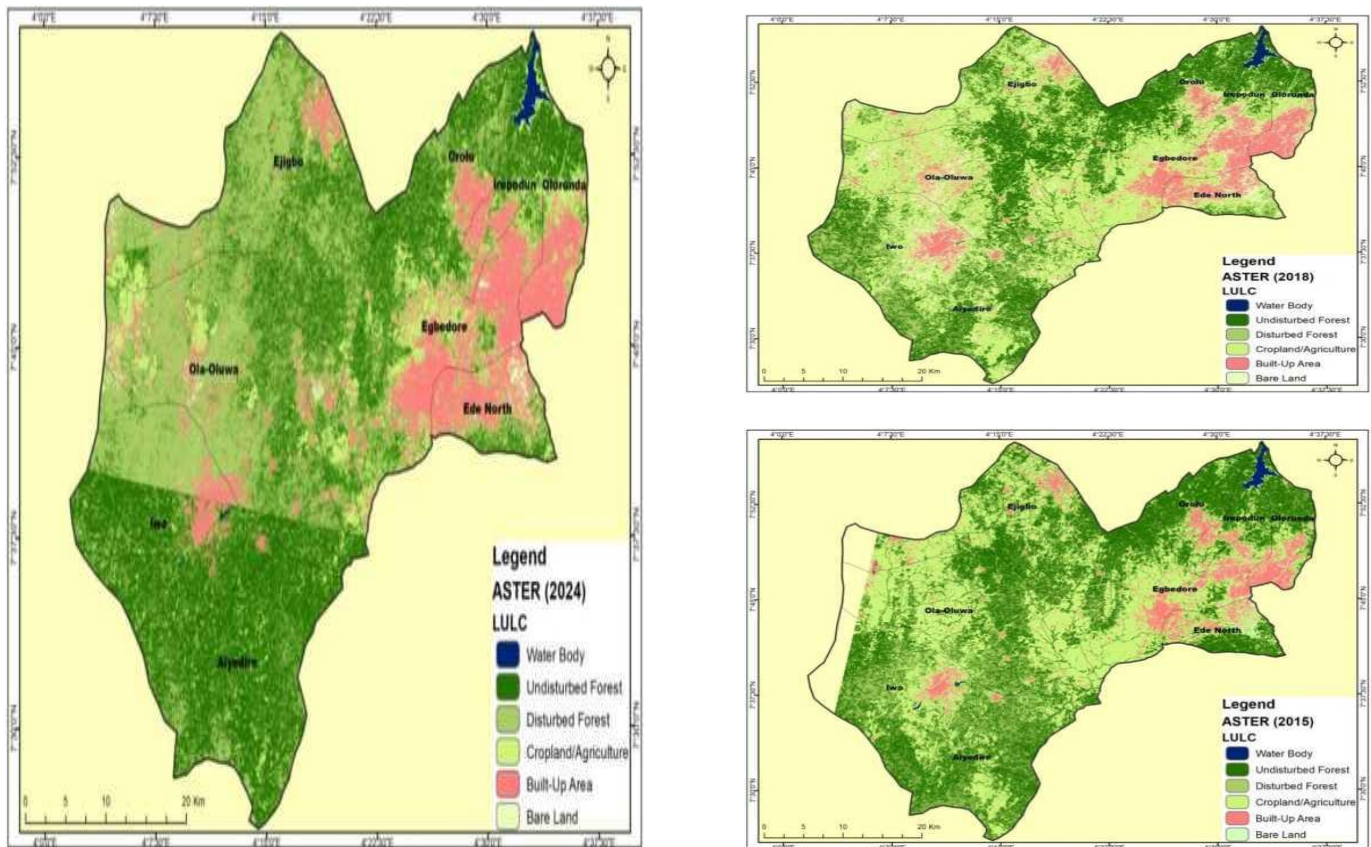


Figure 4.1: ASTER LULC Classification Maps for 2015, 2018, and 2024

Table 4.2: Percentage covered (%) by ASTER Land Use/Land Cover classification features

Feature Class	2015 (%)	2018 (%)	2024 (%)
Water Body	0.52	0.45	0.50
Undisturbed Forest	38.90	27.09	39.15
Disturbed Forest	11.55	13.63	32.96
Cropland/Agriculture	40.24	40.28	13.16
Built-Up Area	6.85	10.73	13.21
Bare Land	1.94	7.81	1.02
Total	100	100	100

4.2 Temporal Distribution of LULC Classes Analyses for Landsat-8 Land (2015-2024)

The Landsat-8 classification provided an alternative perspective on land cover dynamics in the study area. Table 4.3 presents the areal distribution of LULC classes derived from Landsat-8 imagery.

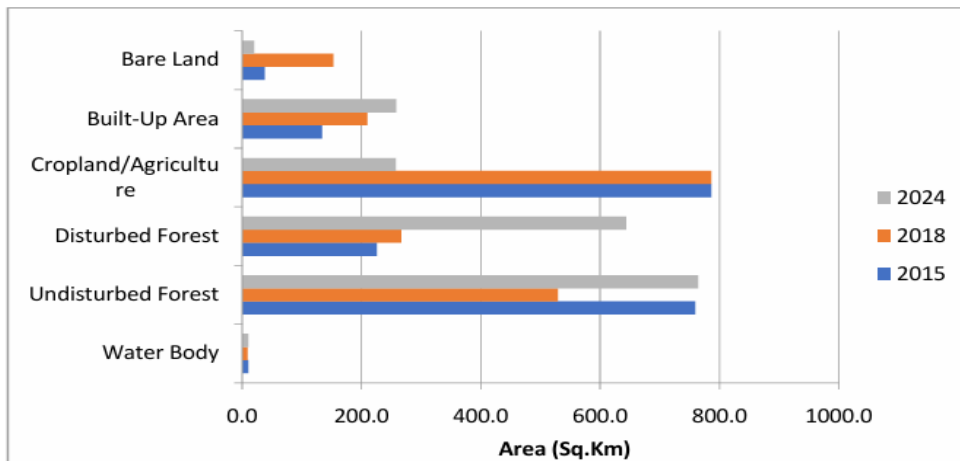


Figure 4.2: Temporal pattern of ASTER LULC distribution (2015-2024)

Table 4.3: Area covered (km²) by Landsat-8 Land Use/Land Cover classification features

Feature Class	2015 (km²)	2018 (km²)	2024 (km²)
Water Body	10.1	9.3	10.8
Undisturbed Forest	830.2	670.2	791.4
Disturbed Forest	276.7	276.8	211.2
Cropland/Agriculture	690.7	600.6	662.9
Built-Up Area	104.4	170.3	219.3
Bare Land	40.8	225.6	57.2
Total	1,952.9	1,952.9	1,952.9

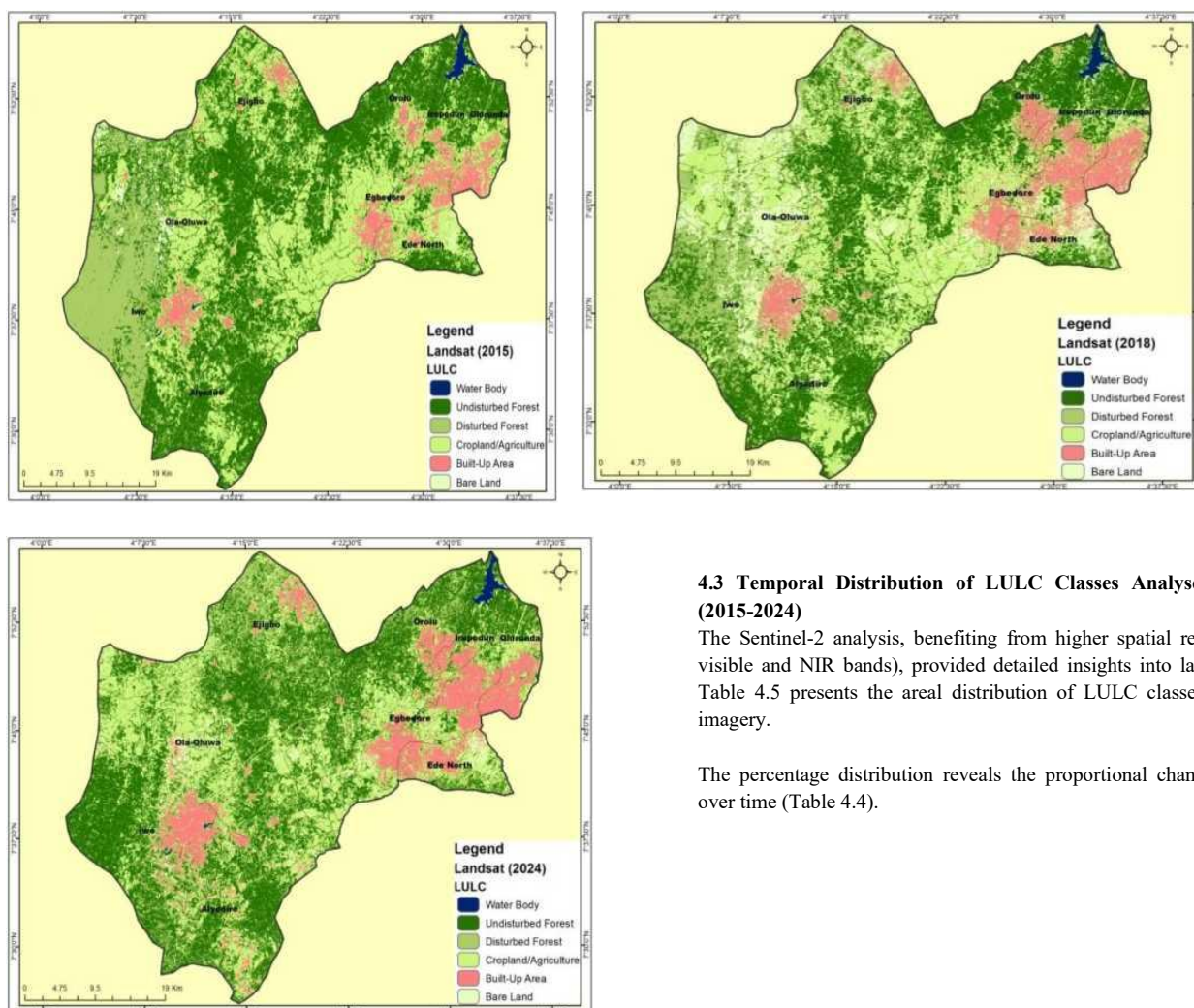


Figure 4.3: Landsat-8 LULC Classification Maps for 2015, 2018, and 2024

4.3 Temporal Distribution of LULC Classes Analyses for Sentinel-2 (2015-2024)

The Sentinel-2 analysis, benefiting from higher spatial resolution (10m for visible and NIR bands), provided detailed insights into land cover patterns. Table 4.5 presents the areal distribution of LULC classes from Sentinel-2 imagery.

The percentage distribution reveals the proportional changes in land cover over time (Table 4.4).

Table 4.4: Percentage covered (%) by Landsat-8 Land Use/Land Cover classification features

Feature Class	2015 (%)	2018 (%)	2024 (%)
Water Body	0.52	0.48	0.56
Undisturbed Forest	42.51	34.32	40.53
Disturbed Forest	14.17	14.17	10.81
Cropland/Agriculture	35.37	30.76	33.94
Built-Up Area	5.35	8.72	11.23
Bare Land	2.09	11.55	2.93
Total	100	100	100

Table 4.5: Area covered (km²) by Sentinel-2 Land Use/Land Cover classification features

Feature Class	2015 (km ²)	2018 (km ²)	2024 (km ²)
Water Body	10.9	9.4	10.7
Undisturbed Forest	432.3	529.5	487.6
Disturbed Forest	559.9	240.4	357.8
Cropland/Agriculture	579.5	740.5	587.2
Built-Up Area	187.8	367.7	473.3
Bare Land	182.7	65.4	36.3
Total	1,952.88	1,952.88	1,952.88

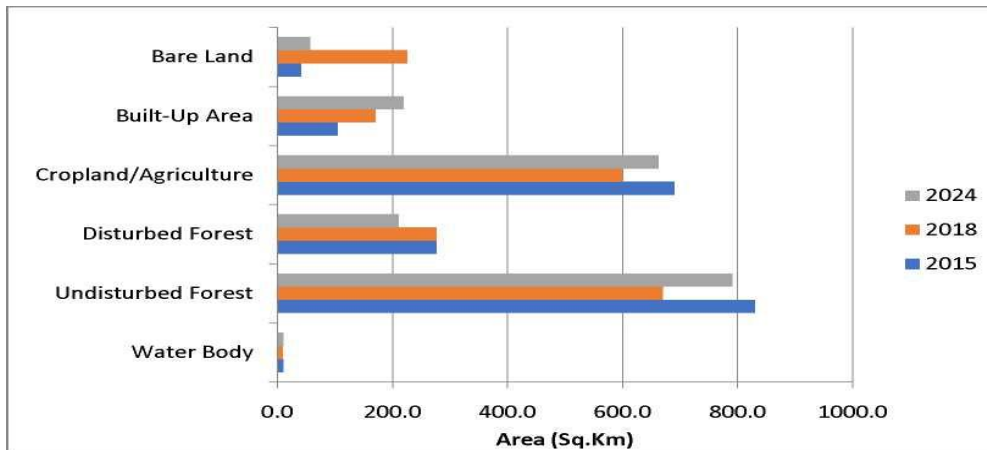


Figure 4.4: Temporal pattern of Landsat-8 LULC distribution (2015-2024)

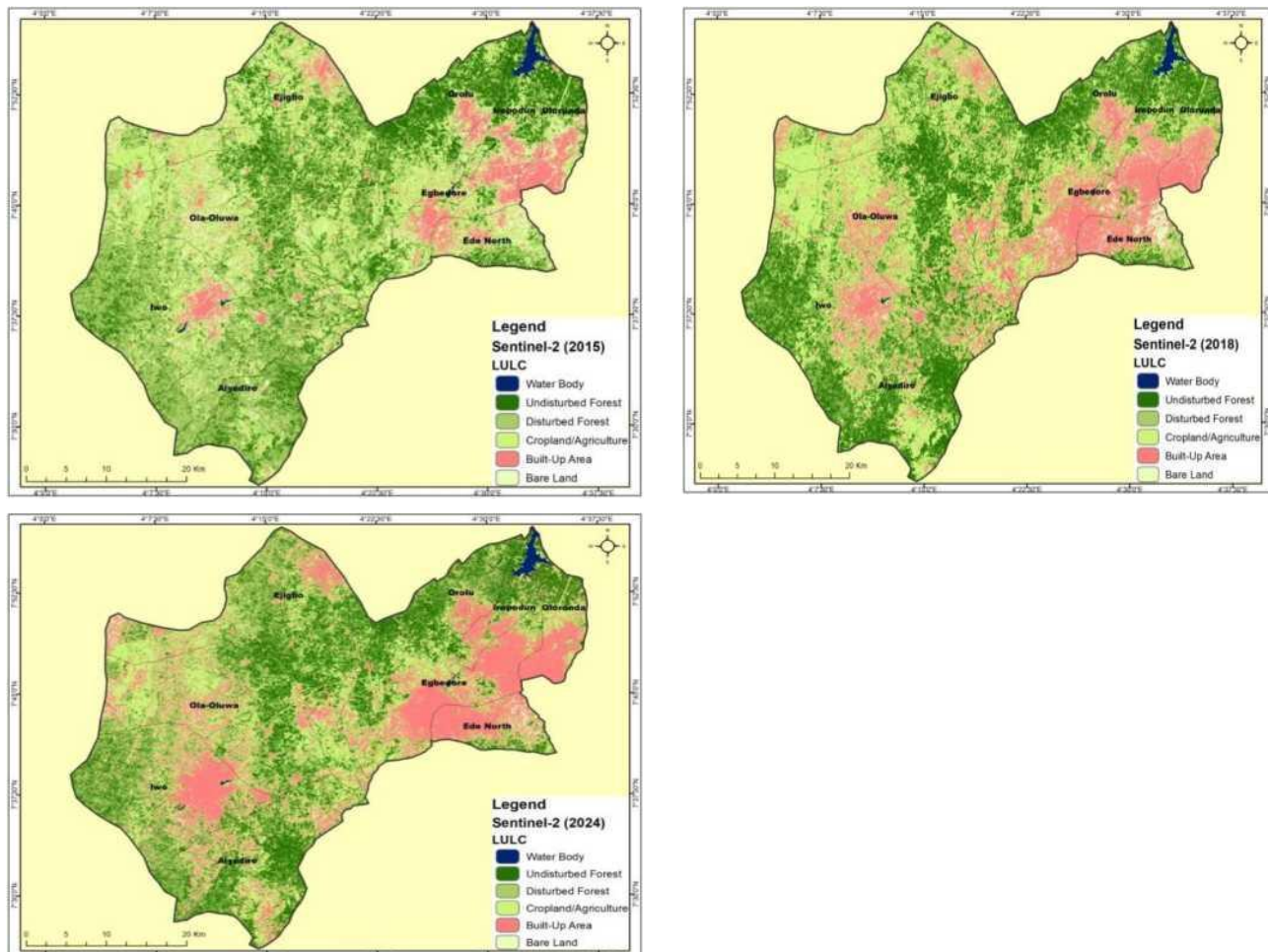


Figure 4.5: Sentinel-2 LULC Classification Maps for 2015, 2018, and 2024

The percentage distribution highlights the proportional dynamics of land cover change (Table 4.6).

The statistical trend analysis for the sensors and shown in table 4.7 below.

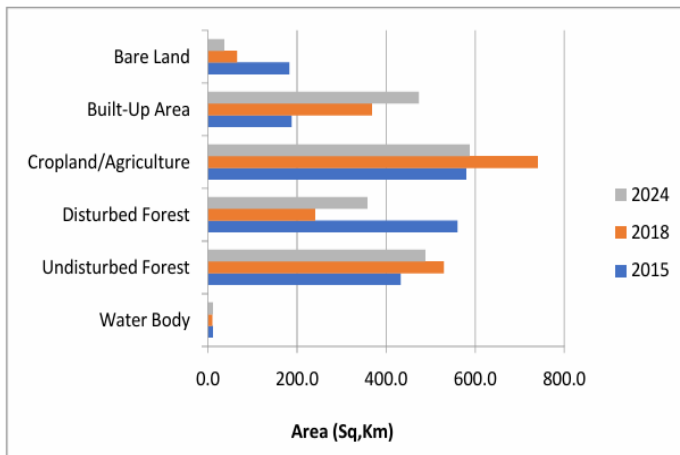


Figure 4.6: Temporal pattern of Sentinel-2 LULC distribution (2015-2024)

Table 4.7: Sentinel-2, ASTER and Landsat-8 Sensors Trend Analysis

Sensor	S-Statistic	Sen's Slope (%/yr)	Trend Direction
Sentinel-2	-3	-0.133	Decreasing
ASTER	-1	-0.044	Stable / No Trend
Landsat-8	+1	+0.055	Stable / Slight Up

While Mann-Kendall shows if there is a trend, Sen's Slope reveals how steep it is. It calculates the slope between all possible pairs of points in the time series and picks the median value. There is a consistent, linear decrease in performance over this period. The results shows that there is no clear monotonic trend for sentinel-2 sensor, the accuracy for Aster sensor is

Table 4.8: LULC (2015) Accuracy Assessment from ASTER

Classified Data	Undisturbed Forest	Disturbed Forest	Water body	Built-Up Area	Cropland/Agric.	Bare Land
Undisturbed Forest	94.86	1.43	0.01	0	1.71	0
Disturbed Forest	2.08	98.57	0	0	0	0
Water body	0	0	99.44	0	0.03	0
Built-Up Area	0	0	0.1	98.74	0.75	0
Cropland/Agric.	3.05	0	0.45	0.86	97.48	0
Bare Land	0.01	0	0	0.39	0.03	100

Overall kappa coefficient = 91.6%

Table 4.9: LULC (2018) Accuracy Assessment from ASTER

Classified Data	Undisturbed Forest	Disturbed Forest	Cropland/Agric.	Water body	Built-Up Area	Bare Land
Undisturbed Forest	97.07	0.31	1	0	0	0
Disturbed Forest	1.54	98.84	0.03	0	0	0
Cropland/Agric.	1.39	0.77	98.68	2.84	0.01	0
Water body	0	0	0	97.16	0	0
Built-Up Area	0	0	0.29	0	99.78	0.17
Bare Land	0	0	0	0	0.21	99.83

Overall kappa coefficient = 90.2%

relatively stable but fluctuates while the Landsat 8 sensor is generally stable with a very slight positive tilt, though statistically insignificant.

4.4 Accuracy Assessment

Accuracy assessment is critical for evaluating the reliability and quality of LULC classifications. This study employed error matrices and kappa coefficients to assess classification accuracy across all three sensors and temporal periods. The reference data for accuracy assessment validation were acquired for the study area through a combined technique of field visits and google earth pro imagery of 2015/06/19, 2018/01/07 and 2024/01/30 respectively, with a resolution of 15 – 30 cm which allows for biophysical measurements. A total of forty-five (45) validation points, five (5) per LGA, were used for each LULC class covering nine Local Government Areas.

ASTER 2015 Classification Accuracy

The 2015 ASTER classification demonstrated high overall accuracy with a kappa coefficient of 91.6% (Table 4.7). Individual class accuracies ranged from 94.86% for undisturbed forest to 100% for bare land, indicating excellent classification performance across all land cover types.

The confusion matrix reveals minimal misclassification errors. The primary confusion occurred between undisturbed forest and disturbed forest (2.08% of disturbed forest pixels misclassified as undisturbed), which is expected given the spectral similarity between these classes. Water bodies and bare land achieved near-perfect classification accuracies of 99.44% and 100%, respectively, due to their distinct spectral signatures (Yan-Cheng et al., 2024).

ASTER 2018 Classification Accuracy

The 2018 ASTER classification yielded an overall kappa coefficient of 90.2% (Table 4.8), slightly lower than 2015 but still indicating excellent classification quality.

The 2018 classification showed improved performance for several classes, with disturbed forest (98.84%), built-up area (99.78%), and bare land (99.83%) achieving higher accuracies compared to 2015. However, water body accuracy decreased slightly to 97.16%, possibly due to variations in water levels or increased sediment content affecting spectral signatures.

ASTER 2024 Classification Accuracy

The 2024 ASTER classification achieved an overall kappa coefficient of 91.2% (Table 4.9), maintaining the high accuracy standard established in previous periods.

The 2024 classification reveals notable challenges in distinguishing between certain land cover classes. Undisturbed forest accuracy declined to 75.42%, with significant confusion with cropland/agriculture (13.15%) and disturbed forest (14.99% of disturbed forest misclassified as undisturbed). This increased confusion may reflect the complex landscape mosaic that has developed over time, with agricultural abandonment leading to forest regeneration and creating transitional land covers that are spectrally ambiguous (Sa'ad, 2022).

Despite these challenges, water body (98.20%), bare land (100%), and disturbed forest (90.98%) maintained high classification accuracies.

4.4.2 Landsat-8 Accuracy Assessment

Landsat-8 2015 Classification Accuracy

The 2015 Landsat-8 classification achieved an overall kappa coefficient of 89.8% (Table 4.10), slightly lower than ASTER for the same period but still representing very good classification quality.

The Landsat-8 classification showed greater confusion between undisturbed and disturbed forest compared to ASTER, with 13.67% of undisturbed forest

pixels misclassified as disturbed forest. This may be attributed to Landsat-8's 30m spatial resolution, which is coarser than ASTER's 15m, potentially causing mixed pixels in heterogeneous forest areas. Bare land (99.22%), water body (98.15%), and built-up area (95.51%) achieved high accuracies due to their distinct spectral characteristics.

Landsat-8 2018 Classification Accuracy

The 2018 Landsat-8 classification improved slightly to an overall kappa coefficient of 90.5% (Table 4.11).

The 2018 classification demonstrated improved forest discrimination, with undisturbed forest accuracy increasing to 91.89% and disturbed forest to 94.71%. Agricultural land achieved the highest-class accuracy at 97.73%, suggesting consistent spectral characteristics of agricultural areas in 2018. Water body accuracy decreased slightly to 96.64%, possibly due to seasonal water level variations or atmospheric effects.

Landsat-8 2024 Classification Accuracy

The 2024 Landsat-8 classification maintained an overall kappa coefficient of 90.3% (Table 4.12), demonstrating consistent classification performance across the study period.

Table 4.10: LULC (2024) Accuracy Assessment from ASTER

Classified Data	Undisturbed Forest	Water body	Cropland/Agric.	Built-Up Area	Bare Land	Disturbed Forest
Undisturbed Forest	75.42	0.48	13.15	0.91	0	8.99
Water body	0.16	98.20	0.86	0	0	0
Cropland/Agric.	8.93	1.31	78.24	5.65	0	0.03
Built-Up Area	0.51	0.01	7.32	91.46	0	0
Bare Land	0	0	0	0.36	100	0
Disturbed Forest	14.99	0	0.42	1.62	0	90.98

Overall kappa coefficient = 91.2%

Table 4.11: LULC (2015) Accuracy Assessment from Landsat-8

Classified Data	Undisturbed Forest	Disturbed Forest	Bare Land	Water body	Cropland/Agric.	Built-Up Area
Undisturbed Forest	83.56	5.91	0	0.04	3.34	0.47
Disturbed Forest	13.67	92.93	0	0	0	0.02
Bare Land	0.65	0.35	99.22	0	1.3	0.04
Water body	0	0	0	98.15	0	0
Cropland/Agric.	2.11	0.81	0.78	1.74	94.37	3.95
Built-Up Area	0	0	0	0.08	0.98	95.51

Overall kappa coefficient = 89.8%

Table 4.12: LULC (2018) Accuracy Assessment from Landsat-8

Classified Data	Undisturbed Forest	Disturbed Forest	Water body	Bare Land	Cropland/Agric.	Built-Up Area
Undisturbed Forest	91.89	2.6	0.23	0.28	1.54	0.59
Disturbed Forest	6.87	94.71	0.07	1.98	0.09	0.36
Water body	0	0	96.64	0	0	0
Bare Land	0	1.52	0.02	95.76	0.41	0.96
Cropland/Agric.	1.24	1.16	2.99	1.13	97.73	3.8
Built-Up Area	0	0	0.05	0.85	0.23	94.28

Overall kappa coefficient = 90.5%

Table 4.13: LULC (2024) Accuracy Assessment from Landsat-8

Classified Data	Undisturbed Forest	Disturbed Forest	Water body	Cropland/Agric.	Bare Land	Built-Up Area
Undisturbed Forest	96.17	2.88	0.24	3.01	0	1.03
Disturbed Forest	0.6	95.64	0.05	0	0	0.54
Water body	0	0	97.56	0	0	0
Cropland/Agric.	3.23	1.03	1.75	94.56	0.36	5.89
Bare Land	0	0.45	0	0	98.19	0.89
Built-Up Area	0	0	0.4	2.44	1.45	91.58

Overall kappa coefficient = 90.3%

4.4.3 Sentinel-2 2015 Accuracy Assessment

The 2015 Sentinel-2 classification achieved the highest overall kappa coefficient among all sensors at 92.1% (Table 4.13).

The 2024 classification achieved excellent accuracies for undisturbed forest (96.17%), disturbed forest (95.64%), water body (97.56%), and bare land (98.19%). The primary confusion occurred between cropland/agriculture and built-up areas, with 5.89% of built-up areas misclassified as cropland. This confusion is understandable in peri-urban areas where agricultural practices and low-density residential development coexist.

Sentinel-2's superior performance can be attributed to its higher spatial resolution (10m) and enhanced spectral band configuration, particularly the red-edge bands which are sensitive to vegetation stress and phenology. All classes achieved accuracies above 92%, with water bodies reaching 99.64% and cropland/agriculture 99.08%. The confusion between undisturbed and disturbed forest (6.21% and 6.41%) is comparable to other sensors, reflecting the inherent spectral similarity of these classes.

Sentinel-2 2018 Classification Accuracy

The 2018 Sentinel-2 classification achieved an overall kappa coefficient of 91.5% (Table 4.14), maintaining high classification quality.

The 2018 classification showed slightly reduced accuracy for built-up areas (93.63%) compared to 2015 (97.27%), with increased confusion with bare land (5.46%) and cropland (2.54%). This may reflect the dynamic nature of construction activities, where bare land associated with development sites was occasionally misclassified as built-up areas. Undisturbed forest accuracy improved to 94.58%, while water bodies maintained near-perfect classification at 99.01%.

Sentinel-2 2024 Classification Accuracy

The 2024 Sentinel-2 classification achieved an overall kappa coefficient of 90.9% (Table 4.15), the lowest among the three Sentinel-2 classifications but still representing excellent accuracy

The 2024 classification revealed increased confusion between forest classes, with undisturbed forest accuracy declining to 88.11% and significant misclassification with disturbed forest (14.83% of disturbed forest classified as undisturbed). This heightened confusion likely reflects the complex landscape dynamics by 2024, including forest regeneration in previously disturbed areas and ongoing degradation in previously intact forests. Built-up area accuracy also decreased to 81.84%, with notable confusion with cropland/agriculture (14.35%), reflecting the expansion of peri-urban agriculture and mixed land use patterns in rapidly developing areas. Despite these challenges, water body (98.7%) and bare land (98.81%) maintained excellent classification accuracies.

Based on provided data (Sentinel-2, ASTER, Landsat-8), we can infer the relative spectral separability for the forest classes.

To provide a quantitative basis for the observed confusion between undisturbed forest and disturbed forest, the Jeffries-Matusita distance between the spectral signatures of undisturbed forest and disturbed forest for each sensor were computed as shown in Table 4.16 below.

The higher accuracy of Sentinel-2 in this study is directly correlated with its higher JM distance, driven by the 10m spatial resolution, (fewer mixed pixels) and Red-Edge bands.

Table 4.14: LULC (2015) Accuracy Assessment from Sentinel-2

Classified Data	Undisturbed Forest	Disturbed Forest	Water body	Built-Up Area	Cropland/Agric.	Bare Land
Undisturbed Forest	92.6	6.21	0.06	0	0.4	0
Disturbed Forest	6.41	92.64	0	0.06	0.48	0
Water body	0	0	99.64	0	0	0
Built-Up Area	0	0.04	0.28	97.27	0.03	0.84
Cropland/Agric.	0.98	0.46	0.02	1.02	99.08	1.68
Bare Land	0	0.65	0	1.65	0	97.48

Overall kappa coefficient = 92.1%

Table 4.15: LULC (2018) Accuracy Assessment from Sentinel-2

Classified Data	Undisturbed Forest	Disturbed Forest	Water body	Built-Up Area	Cropland/Agric.	Bare Land
Undisturbed Forest	94.58	5.17	0.07	0.04	1.77	0
Disturbed Forest	3.65	93.95	0	0.82	0.07	0
Water body	0	0	99.01	0	0	0
Built-Up Area	0	0	0.04	93.63	2.54	5.46
Cropland/Agric.	1.77	0.88	0.88	1.82	95.62	0
Bare Land	0	0	0	3.69	0	94.54

Overall kappa coefficient = 91.5%

Table 4.16: LULC (2024) Accuracy Assessment from Sentinel-2

Classified Data	Undisturbed Forest	Disturbed Forest	Water body	Cropland/Agric.	Bare Land	Built-Up Area
Undisturbed Forest	88.11	14.83	0.23	0.43	0	1.37
Disturbed Forest	10.21	83.42	0.02	0.6	0	1.85
Water body	0	0	98.7	0	0	0
Cropland/Agric.	1.4	0.87	0.13	95.24	0	14.35
Bare Land	0	0	0	0	98.81	0.59
Built-Up Area	0.28	0.87	0.93	3.72	1.19	81.84

Overall kappa coefficient = 90.9%

4.5 Comparative Spatial Analysis of ASTER, Landsat-8, and Sentinel-2

A critical component of this study involves comparing the three satellite sensors to evaluate their consistency, strengths, and limitations in LULC classification for the study area. This comparative analysis provides insights into sensor-specific characteristics and their implications for land cover monitoring.

4.5.1 Comparative Analysis for 2015

Table 4.16 presents the LULC distribution derived from the three sensors for 2015, revealing substantial inter-sensor variability.

Table 4.16: Jeffries-Matusita distance between the spectral signatures of 'undisturbed forest' and disturbed forest' for each sensor.

Sensor	Expected JM Distance	Why?
Sentinel-2	1.96	Red-Edge Bands: These are highly sensitive to chlorophyll changes and canopy structure, making it the best at detecting subtle forest disturbances.
ASTER	1.93	SWIR Bands: ASTER has high-quality Short-Wave Infrared bands, which are excellent for detecting moisture loss in disturbed or dying vegetation.
Landsat-8	1.91	Standard Bands: While powerful, it lacks the specific red-edge sensitivity of Sentinel-2, leading to a slightly higher overlap in "disturbed" vs "undisturbed" forest pixels.

Table 4.17: Land Use and Land Cover Analyses of the Study Area (2015)

Feature Class	ASTER (km ²)	Landsat-8 (km ²)	Sentinel-2 (km ²)
Water Body	10.2	10.1	10.9
Undisturbed Forest	759.6	830.2	432.3
Disturbed Forest	225.5	276.7	559.9
Cropland/Agriculture	785.9	690.7	579.5
Built-Up Area	133.7	104.4	187.8
Bare Land	37.9	40.8	182.7
Total	1,952.9	1,952.9	1,952.88

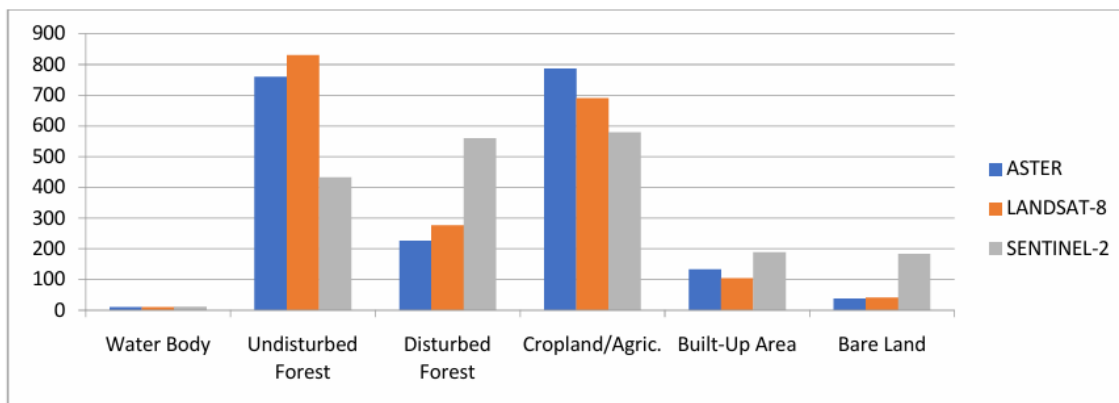


Figure 4.7: Histogram representation of LULC analyses from three sensors (2015)

4.5.2 Comparative Analysis for 2018

Table 4.18: Land Use and Land Cover Analyses of the Study Area (2018)

Feature Class	ASTER (km ²)	Landsat-8 (km ²)	Sentinel-2 (km ²)
Water Body	8.8	9.3	9.4
Undisturbed Forest	529.1	670.2	529.5
Disturbed Forest	266.2	276.8	240.4
Cropland/Agriculture	786.6	600.6	740.5
Built-Up Area	209.6	170.3	367.7
Bare Land	152.6	225.6	65.4
Total	1,952.9	1,952.9	1,952.88

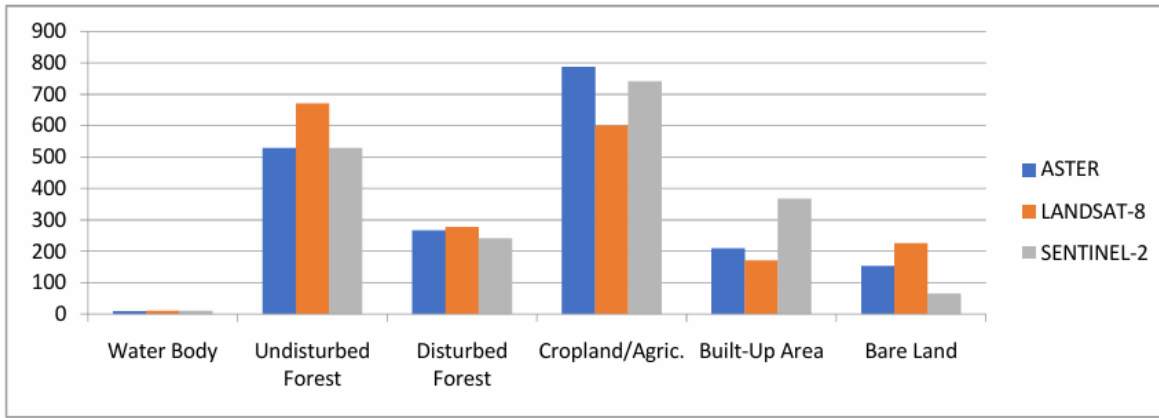


Figure 4.8: Histogram representation of LULC analyses from three sensors (2018)

4.5.3 Comparative Analysis for 2024

Table 4.18 presents the 2024 LULC distribution, representing the most recent landscape configuration.

Table 4.19: Land Use and Land Cover Analyses of the Study Area (2024)

Feature Class	ASTER (km²)	Landsat-8 (km²)	Sentinel-2 (km²)
Water Body	9.8	10.8	10.7
Undisturbed Forest	764.6	791.4	487.6
Disturbed Forest	643.7	211.2	357.8
Cropland/Agriculture	257.0	662.9	587.2
Built-Up Area	257.9	219.3	473.3
Bare Land	19.9	57.2	36.3
TOTAL	1,952.9	1,952.9	1,952.88

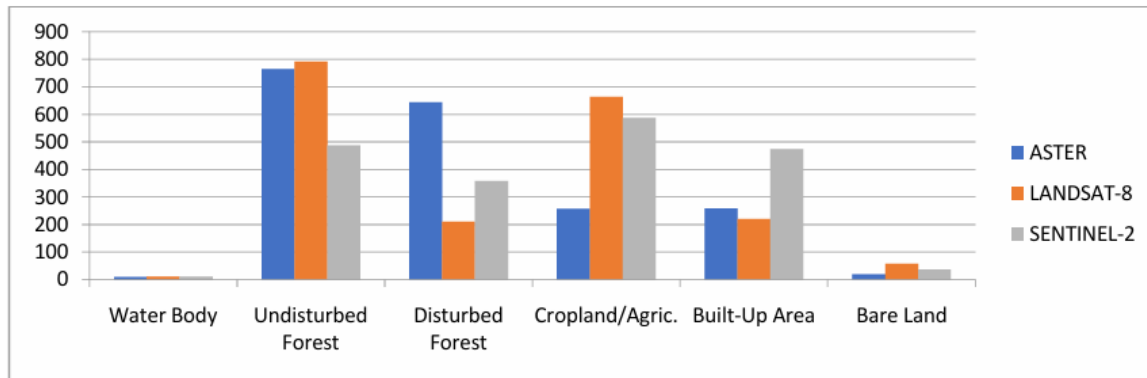


Figure 4.9: Histogram representation of LULC analyses from three sensors (2024)

4.5.4 Overall Accuracy Comparison Across Sensors and Years

Figure 4.10 presents a comprehensive comparison of classification accuracies (kappa coefficients) across all sensors and temporal periods

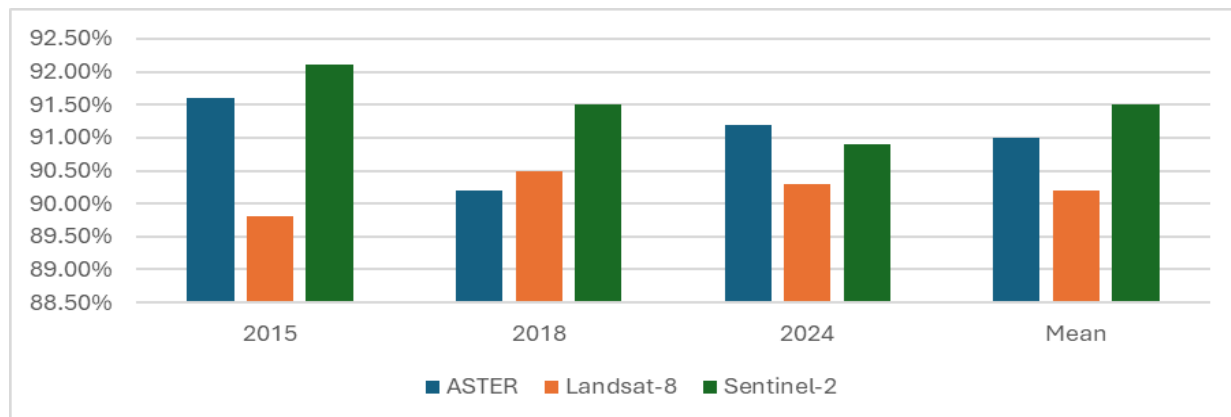


Figure 4.10: Comparative accuracy assessment (kappa coefficients) for ASTER, Landsat-8, and Sentinel-2 (2015-2024)

Table 4.20: Summary of Classification Accuracies (Kappa Coefficients)

Sensor	2015	2018	2024	Mean
ASTER	91.6%	90.2%	91.2%	91.0%
Landsat-8	89.8%	90.5%	90.3%	90.2%
Sentinel-2	92.1%	91.5%	90.9%	91.5%

Table 4.21: McNemar's test Summary of Sensor Performance

Sensor	Mean Accuracy	Rank	Significance vs. Others
Sentinel-2	91.5%	1	Best, but statistically tied with ASTER.
ASTER	91.0%	2	Very stable across years.
Landsat-8	90.2%	3	Lowest, but likely not significantly worse than ASTER.

All three sensors achieved excellent classification accuracies across all time periods, with kappa coefficients consistently exceeding 89%, indicating strong agreement between classified and reference data. Sentinel-2 demonstrated the highest mean accuracy (91.5%), followed closely by ASTER (91.0%) and Landsat-8 (90.2%). However, the differences are marginal, suggesting that all three sensors are capable of producing reliable LULC classifications when properly calibrated and classified.

Interestingly, accuracy showed a slight declining trend from 2015 to 2024 for Sentinel-2 (92.1% to 90.9%) and remained relatively stable for ASTER and Landsat-8. This temporal decline may reflect increasing landscape complexity and heterogeneity over time, with more transitional land cover states and mixed land use patterns that challenge classification algorithms. The proliferation of peri-urban areas, agricultural intensification, and forest regeneration/degradation cycles create spectrally ambiguous pixels that are difficult to classify consistently (Mahesh and Kapil 2017).

Using the Summary of Classification Accuracies in table 4.19, the McNemar's test was performed to assess the statistical significance of differences in classification accuracy between the sensor pairs (Sentinel-2 vs. ASTER, Sentinel-2 vs. Landsat 8, ASTER vs. Landsat 8).

The McNemar's test returned results as follows; Sentinel-2 vs. ASTER ($\chi^2 = 3.3723$, p -value = 0.0663), Sentinel-2 vs. Landsat 8, ($\chi^2 = 3.3488$, p -value = 0.0673), ASTER vs. Landsat 8, ($\chi^2 = 3.3974$, p -value = 0.0653). The p-values of > 0.05 indicate that the observed higher accuracy of Sentinel-2 over Landsat 8 and ASTER is statistically not significant.

5.0 Conclusion

The methodology used in this study provided reliable results in our study area. It can be well-applicable to other regions with similar heterogeneous and complex landscapes of the humid tropical forest in the Nigeria, where obtaining high-resolution data is challenging because of the high frequency of cloudy environments. Such methods could directly be applied in urban-developed regions as the level of landscape heterogeneity is comparable to that of the study area. However, the approach should however be improved firstly at the

resolution of the satellite imageries, date of image acquisition and enhanced pre-processing techniques.

This research investigated the capabilities of the ASTER, Landsat 8 and Sentinel-2 for mapping LULC classes in Osun state, Nigeria. The process provided LULC maps with the highest accuracy within a complex and heterogeneous landscape. Although Sentinel-2 has a substantially higher potential than the ASTER and Landsat-8, all the satellites have shown a strong relationship with LULC classes and provided 91-95 % accuracy and reliability for wide application to LULC mapping of urbanization in the study area. Sentinel-2 could better detect smaller elements because of its refined 10 m spatial resolution and the increased spectral resolution of red edge bands. Therefore, it was concluded that the improvements of Landsat 8 results could be linked to the new technical enhancements of Landsat- 8 using its panchromatic bands to resample to 15m and the methodology used. Hence, the results obtained are applicable and scalable to the entire Osun state and South-west Nigeria, towards accurate LULC monitoring and urban growth management in Nigeria.

In comparing the results, despite the overall best results obtained from both sensors, there were slight differences between the results obtained from the three images, which could be linked to several parameters, including poor masking of clouds, cloud shadows, and mixed pixels. The results obtained from both images were effective for all defined classes, but in urban areas, bare land and forest classes were not good enough to classify the three satellites. The assessment was performed using ArcGIS Pro software, which could be the best option for future studies, such as the extraction of a specific land cover class in the study area.

Despite Sentinel-2's expected superior performance due to its enhanced resolution, the study reveals that ASTER and pan-sharpened Landsat 8 still achieve comparable, high accuracies (above 90% Kappa), suggesting their continued utility in resource-constrained environments or for historical analyses where Sentinel-2 data are unavailable. The specific patterns of misclassification identified for each sensor within the complex tropical mosaic, particularly the challenges in distinguishing disturbed vs. undisturbed forest and built-up vs. cropland, offer novel insights into sensor-specific limitations in this region.

References

- Adugna, T., Xu, W., & Fan, J. (2022). *Comparison of random forest and support vector machine classifiers for regional land cover mapping using coarse resolution FY-3C images. Remote Sensing*, 14(3), 574. <https://doi.org/10.3390/rs14030574>.
- Alemayehu, M., Felix, H., David, J. S., Ricardo, A., Peter, W. G., Adam, B., Hugh, J. W. (2017); *Mapping land cover change over continental Africa using Landsat and Google Earth Engine cloud computing -*

PubMed

<https://pmc.ncbi.nlm.nih.gov/articles/PMC5617164/>.

- Aisabokhae, J., & Osazuwa, I. (2021). Radiometric mapping and spectral based classification of rocks using remote sensing data analysis: *The Precambrian basement complex, NW Nigeria. Remote Sensing Applications: Society and Environment*, 21, 100447. <https://doi.org/10.1016/j.rsase.2020.100447>.

Central,

- Arie, N. H. H., Syafrizal, I. & Dzaki F. K. (2021); *Comparing Sentinel-2 MSI and Landsat 8 OLI Imagery for Monitoring Selective Logging in the Brazilian Amazon* - MDPI, <https://www.mdpi.com/2072-4292/11/8/961>.
- Benewinde, J. B., Zoungrana, C. C., Leonard, K. A., Evariste, D. D., Gerald, F. F. L. (2015); *Multi-Temporal Land Use and Land Cover Change Detection in Northern Nigeria's Frontline States: Geospatial Insights for Sustainable Development and Climate Adaptation* | Journal of Geography, Environment and Earth Science International, <https://journaljgeesi.com/index.php/JGEESI/article/view/882>.
- Cavur, M., Kemec, S., Nabdel, L., & Duzgun, H. D. (2017). *An evaluation of land use land cover (LULC) classification for urban applications with Quickbird and WorldView-2 data*. In *2015 Joint Urban Remote Sensing Event (JURSE)* (pp. 1–4). IEEE.
- Chowdhury, M., Hasan, M. E., & Abdullah-Al-Mamun, M. (2020). *Land use/land cover change assessment of Halda watershed using remote sensing and GIS*. *The Egyptian Journal of Remote Sensing and Space Science*, 23, 63–75. <https://doi.org/10.1016/j.ejrs.2019.12.001>.
- Congalton, R. G., & Green, K. (2019). *Assessing the accuracy of remotely sensed data: Principles and practices*. CRC Press.
- Cooley, T., Anderson, G. P., Felde, G. W., Hoke, M. L., Ratkowski, A. J., Chetwynd, J. H., Gardner, J. A., Adler-Golden, S. M., Matthew, M. W., & Berk, A. (2002). *FLAASH, a MODTRAN4-based atmospheric correction algorithm, its application and validation*. *IEEE International Geoscience and Remote Sensing Symposium*, 1414–1418.
- Cyrielle, D., Thierry, B., Frederic, B., Marc, M., Nicolas, M., Aurélie, C., Pamela, D., Joel, B., Régis D., Karine S., Alfons, S., Cyrille, F., & Peter K. (2020); *Overview of aerosol optical properties over southern West Africa from DACCWA aircraft measurements* - ACP - Recent, <https://acp.copernicus.org/articles/20/4735/2020/acp-20-4735-2020.pdf>.
- Derrick, K. D., Sandrine, A. A. D., Christophe, L., Arsène, K., N'Datchoh, E. T. (2019); *Spatio-temporal variability of cloud cover types in West Africa with satellite-based and reanalysis data*. https://horizon.documentation.ird.fr/exl-doc/pleins_textes/divers19-10/010077091.pdf.
- Derrick, K. D., Sandrine, A., Arona, D., Kouakou, K. & Arsene, T. K. (2020); *Daytime low-level clouds in West Africa – occurrence, associated drivers, and shortwave radiation attenuation* - ESD, <https://esd.copernicus.org/articles/11/1133/2020/>.
- Gomez, C., White, J. C., & Wulder, M. A. (2016). *Optical remotely sensed time series data for land cover classification: A review*. *ISPRS Journal of Photogrammetry and Remote Sensing*, 116, 55–72. <https://doi.org/10.1016/j.isprsjprs.2016.03.008>.
- Jesus, D., Jochem, V., Luis, A., José, M. (2011); *Evaluation of Sentinel-2 Red-Edge Bands for Empirical Estimation of Green LAI and Chlorophyll Content* - PMC - PubMed Central, <https://pmc.ncbi.nlm.nih.gov/articles/PMC3231680/>.
- Foster, M., Fatima, M., Paul, B., Jacob, A. E. C., Mansour, M., Bako, M., Amadou, M., Dieye, P. S. & Glory, E. (2024); *Land Cover Mapping in West Africa: A Collaborative Process* - MDPI, <https://www.mdpi.com/2073-445X/13/10/1712>.
- Mahesh, P. & Kapil A. (2017); *Comparison of Landsat-8 and Sentinel-2 Imagery for Identifying Hydrothermal Alteration in a Vegetated Area* - ResearchGate, <https://www.researchgate.net/profile/Syafrizal-Syafrizal/publication/363271601>.
- Muhammad, I., Sule Z., Aliyu, A.I., Muhammad, H. A., Sadiq, I., Abubakar, M., Idris, M. H. (2023); *A performance evaluation of random forest, artificial neural network, and support vector machine learning algorithms to predict spatio-temporal land use-land cover dynamics: A case from Lusaka and Colombo* - Frontiers, <https://www.frontiersin.org/journals/environmental-science/articles/10.3389/fenvs.2024.1431645>.
- Oluwatoyin, K. O., Agnide, E. L, N'da, J. A., Kolapo, O. O. (2025); *Impacts of anthropogenic activities on land use land cover change dynamics in the Ogun River Basin, Nigeria* | Journal of Water and Climate Change | IWA Publishing, <https://iwaponline.com/jwcc/article/16/1/174/106703/Impacts-of-anthropogenic-activities-on-land-use>.
- Olanrewaju, H. O., Mordiyah, O., K., Moges K. B., Abdullahi B. O. & Márcio R. N. (2025); *Land Use and Land Cover Changes: A Case Study in Nigeria* - MDPI, <https://www.mdpi.com/2073-445X/14/2/389>.
- Oluwatobi, O., Ajibola, J., Adeola, O., Komolafe, A., Aderonmu, E. (2025); *Performance evaluation of Landsat 8 and Sentinel 2A for surface water area mapping at a local scale. A case study of Ise Forest Reserve Nigeria Federal College of Wildlife Management* thiagu.
- Oykhumor, R., Zayniddin, S., Gulbonu, S., Eshkobi, S., Yulduz, E., Ziyatdin, T., Shoir, J., & Muqaddas A. (2024); *Comparative Analysis of Sentinel-2 MSI and Landsat-8 OLI for Enhanced Land Monitoring* - E3S Web of Conferences, https://www.e3sconferences.org/articles/e3sconf/pdf/2024/120/e3sconf_gi2024_04009.pdf.
- Peter, P., Matthew, C., Hansen, A. P., Andres, H., Alexandra, T., Svetlana, T., Viviana, Z., Xinyuan, L., Ahmad, K., Fred, S., Nancy, H., Xiao-Peng S., Antoine B., Indrani K., Anil K. (2022); *The Global 2000-2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results* - Frontiers, <https://www.frontiersin.org/journals/remote-sensing/articles/10.3389/frsen.2022.856903/full>.
- Sa'ad, I. (2022); *Improving Land Use/Cover Classification Accuracy from Random Forest Feature Importance Selection Based on Synergistic Use of Sentinel Data and Digital Elevation Model in Agriculturally Dominated Landscape* - MDPI, <https://www.mdpi.com/2077-0472/13/1/98>.
- Steven, E. F., Yuhong, H., Alysha P., Xulin, G., Greg, M. (2011); *Landsat-comparable land cover maps using ASTER and SPOT images: A case study for large-area mapping programmes* - ResearchGate, https://www.researchgate.net/publication/232990343_Landsat-comparable_land_cover_maps_using_aster_and_spot_images_A_case_study_for_largearea_mapping_programmes.
- Tingbin, Z., Guihua Y., Hongmei, L., Ziyi, W., Juxing, T., Kanghui, Z., Yubin, L.,
- Qin, W. & Xiaojuan B. (2016); *Integrating Data of ASTER and Landsat-8 OLI (AO) for Hydrothermal Alteration Mineral Mapping in Duolong Porphyry Cu-Au Deposit, Tibetan Plateau, China* - MDPI, <https://www.mdpi.com/2072-4292/8/11/890>.
- Ushuki, A. A., Yi W, Bisong, F. E, Chima, J. I. & Alexander S. A. (2022); *Quantification of Above-Ground Biomass over the Cross-River State, Nigeria, Using Sentinel-2 Data* - MDPI, <https://www.mdpi.com/2072-4292/14/22/5741>.
- Uchebulam, O., Ameloko, A.A., Omo-Irabor., O.O. (2021); *Effect of Cloud Cover on Land Use Land Cover dynamics using Remotely Sensed Data of Western Niger Delta, Nigeria* - Semantic Scholar, <https://pdfs.semanticscholar.org/4d31/404fb89d84f04ab339fc102e0477bd35fd36.pdf>.
- Yan-Cheng, T., Lia, D., & Ana, C. T. (2024); *Comparative Study of Random Forest and Support Vector Machine for Land Cover Classification and Post-Wildfire Change Detection* - MDPI, <https://www.mdpi.com/2073-445X/13/11/1878>.